Research Statement

Kevin He
October 21, 2018

I specialize in microeconomic theory and behavioral economics. Recently, I have studied the implications of multi-agent learning in settings with populations of rational or behavioral learners. My projects in behavioral learning focus on how behavioral biases interact with features of the learning environment. My projects in rational learning center around the implications of non-equilibrium learning for equilibrium refinements. A common theme in these two strands is an emphasis on the dynamics of learning.

My job-market paper [1] studies endogenous learning dynamics for people who expect systematic reversals from sequential random events (the “gambler’s fallacy”). Specifically, I consider a population of agents taking turns playing the same dynamic stage game, an optimal-stopping problem (e.g. managers conducting sequential interviews before making an offer). Initially, agents are uncertain about the distributions generating draws in the stage game (e.g. the distribution of talent in the labor pool). Agents use others’ histories to make inferences about these distributions, but exaggerate how unlikely it is to get consecutive bad draws due to their statistical bias. The crux of this setting is the interaction between misspecified learning (no feasible belief of the biased agents exactly matches observations, due to their false expectation of reversals) and endogenous data censoring (past histories are censored by past agents’ stopping strategies, which are derived from these predecessors’ beliefs). When a sequence of biased agents play stage game one by one, society almost surely converges to a unique steady state where agents hold overly pessimistic beliefs and stop too early. The intuition is that agents rationally stop after “good enough” early draws, endogenously imposing an asymmetric censoring effect on history. Later draws are only observed following bad early draws, so biased agents expect positive reversals in others’ histories. The absence of these expected reversals in data leads to pessimistic inference. Now suppose agents arrive in large generations, with all agents in the same generation acting simultaneously. Then society converges monotonically across generations to the same steady state as the previous environment, given any initial condition. In particular, a society initiated at the objectively optimal strategy incurs strictly increasing amounts of welfare loss across all successive generations, as endogenous learning amplifies the misinference of earlier biased agents through a positive-feedback loop between distorted beliefs and distorted stopping strategies.

My joint work with Krishna Dasaratha [2] considers a different behavioral bias in the context of sequential social learning. Agents live on a social network and move one at a time, making guesses about a state of the world based on: (i) the guesses of neighbors who moved before, (ii) own private signals. Agents have inferential naiveté, wrongly believing their predecessors acted solely on private information. We show almost all networks lead to imperfect learning for naive agents, then study how different networks lead to differentially inefficient outcomes. To do this, we go beyond existing results and compute the exact probability of correct learning on a given network. The probability of correct learning is lower on denser networks — we confirm this prediction using an experiment, finding people’s accuracy gain from learning is twice as large on sparser networks. In partially segregated networks, divergent early signals can lead to persistent disagreement between groups — a common empirical phenomenon that is hard to reconcile with rational social-learning models.
In the area of rational multi-agent learning, I have completed a cluster of interrelated projects on the refinement implications of learning-in-games, coauthored with Drew Fudenberg. The main idea is that if equilibrium originates from learning, then we can refine the prediction set by ruling out the equilibria that learning cannot converge to. Suppose large populations of patient, long-lived senders and receivers are randomly matched to play a signaling game each period. Young senders are uncertain about how receivers react to different signals, generating experimentation incentives. In [3], we characterize which sender types rationally experiment more with each (possibly off-path) signal during the learning process. This implies a compatibility-criterion restriction on the receivers’ off-path beliefs. In particular, every learning outcome satisfies the Intuitive Criterion. In [4], we obtain further refinements by assuming agents know others’ rationality and utility functions. (These projects apply our statistical results about Bayesian inference after rare events [5], with Lorens Imhof. In this setting, the rare event corresponds to the uncommon but positive-probability event of a receiver observing an “off-path” signal during learning.) In [6], we consider general games and propose a tremble-based solution concept with cross-player restrictions on the relative magnitudes of trembles. Our concept picks out intuitive equilibria in games where other tremble-based concepts have no bite. We show rational learning and some near-optimal heuristics imply our tremble restrictions.

Much of my work has revolved around analyzing the dynamics of learning, both as tools for studying the limit properties of learning and as objects of interest in their own right. For example, [3] compares the optimal experimentation dynamics of different types of senders to deduce which beliefs and equilibria can arise in the long-run limit of learning. In [1], the large-generations learning dynamics provide a richer characterization of how welfare loss evolves over time and clarify the interaction between the statistical bias and endogenous data. I plan on exploring this theme further in future work.

References


